Information Retrieval

Oct 1, 2024 @ Introduction to Human Language Technology

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Slides borrowed from SIGIR24 Tutorial "Neural Methods for Cross-Language Information Retrieval"

What is Information Retrieval? (relevant)

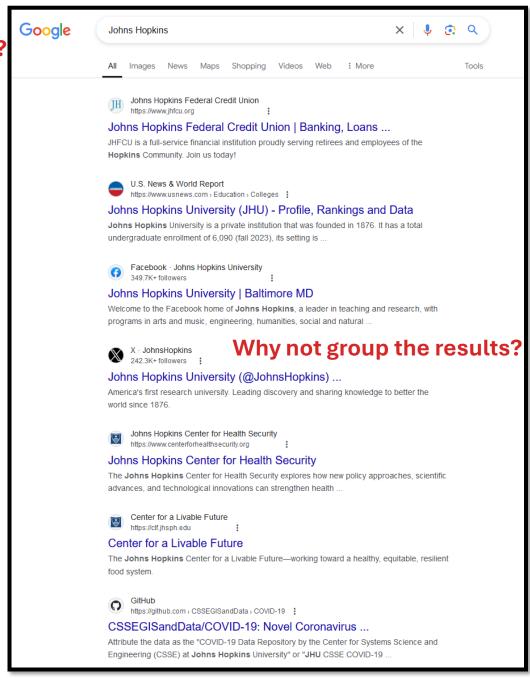
Retrieve information from a storage based on user's information need

Don't we have Google?

Yes, but Google is not all.

What if I'm looking for the person?





Why not read my mind?

Why asking me to read?

Google Search is just one implementation

Google trained us well!

- Even faster?
- Smarter?
- Cross language?

Hard Matching Problem

- Text to text
 - Search in notes
 - Cross language search
 - Cross domain search
- Text to other modalities
 - Image search
 - Video search

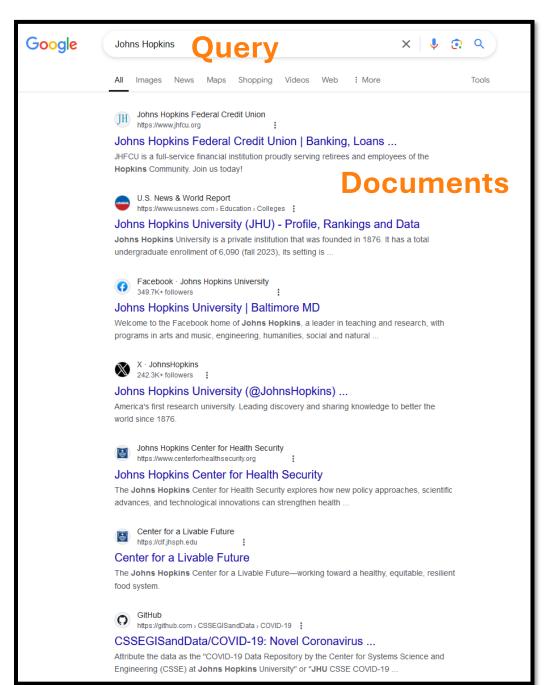
Different Search Process

- Iterative search
 - e.g., electronic discovery and systematic review
- Conversational search
 - Alexa search
- Recommendation systems
- (Set Retrieval)

Core Problem

- Matching problem
- Do it fast

Ranked List



Agenda

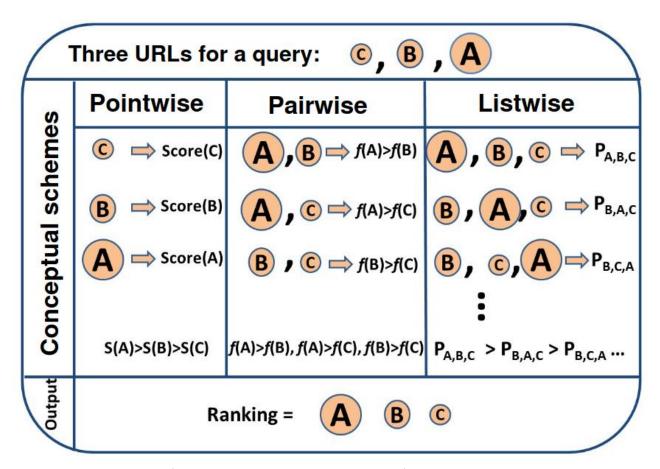
- What is information retrieval?
- Retrieval Modeling and Pipeline
 - Statistical and Neural
- Evaluation
- State of IR Research and active research problems

Retrieval Modeling and Pipeline

Three main ways

- Pointwise
- Pairwise
- Listwise

And combinations of them



https://medium.com/vptech/learning-to-rank-at-veepee-ed420fd828e5

Statistical Models

$$score(D,Q) = \sum$$
 How important the term is x How often the term appear in the D For each query term

$$score(D, Q) = \sum$$
 Inverted document frequency x Term frequency

For each query term

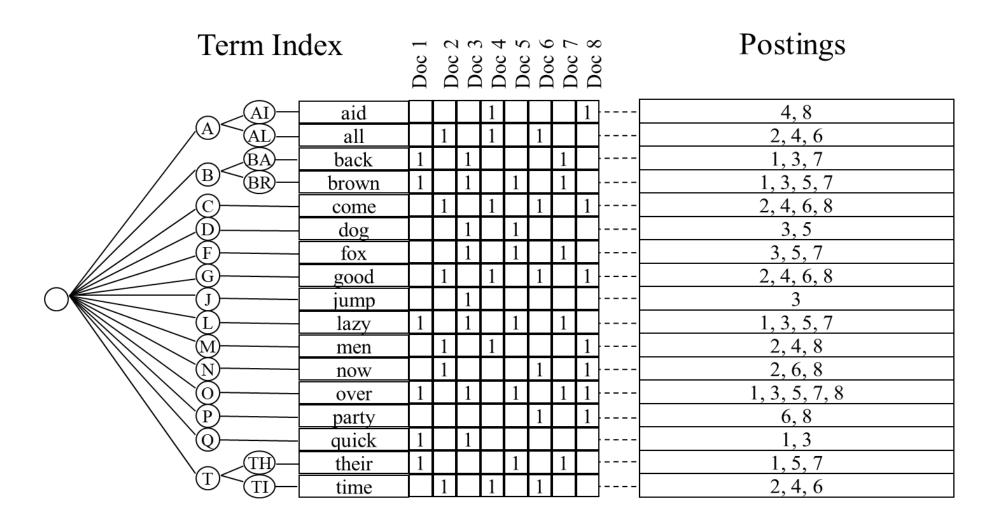
TF-iDF
$$score(D, Q) = \sum_{i=1}^{n} log \frac{N}{n_t} \times log(f(q_i, D) + 1)$$

$$extstyleset{ extstyleset} extstyleset{ extst$$

How to make it fast?

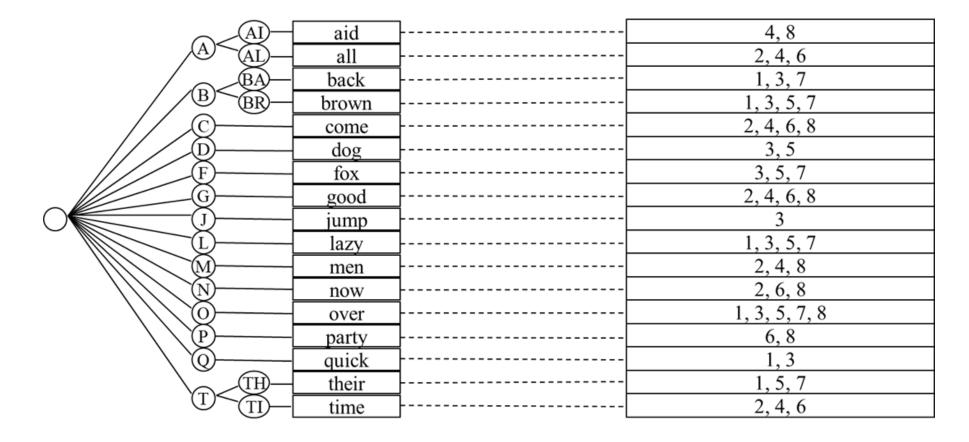
- "Fast" in responding to queries
- Better data structure
- Preprocess the data

Inverted Index



Inverted Index

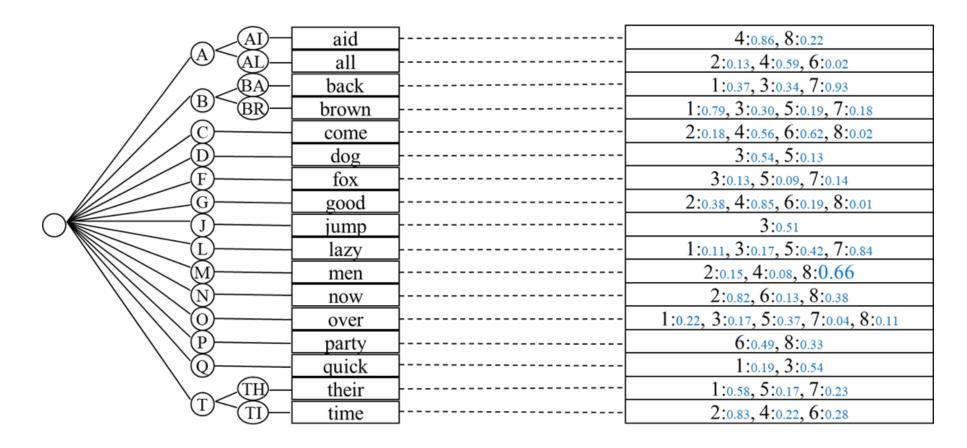
Term Index Postings



Inverted Index

Term Index

Postings



Two-Stage System

- Offline preprocessing and indexing
 - Build the inverted index
- Online query serving
 - Traverse the inverted index and score it



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Apache Lucene is distributed under a commercially friendly Apache Software license

Elasticsearch

The heart of the free and open Elastic Stack

 ${\it Elastic search is a distributed, RESTful search and analytics engine, scalable data}$

store, and vector database capable of addressin the heart of the Elastic Stack, it centrally store fine-tuned relevancy, and powerful an



Download Elastic

Welcome to Apache Lucene

The Apache Lucene™ project develops open-source search software. The project releases a core search library, named Lucene™ core, as well as PyLucene, a python binding for Lucene.

Lucene Core is a Java library providing powerful indexing and search features, as well as spellchecking, hit highlighting and advanced analysis/tokenization capabilities. The PyLucene sub project provides Python bindings for Lucene Core.

Latest Lucene Core News

Apache Lucene™ 8.11.4 available (24.Sep)

Apache Lucene™ 9.11.1 available (27.Jun)

Apache Lucene™ 9.11.0 available (06.Jun)

Projects

Lucene Core (Java)
PyLucene
Open Relevance
(Discontinued)

About

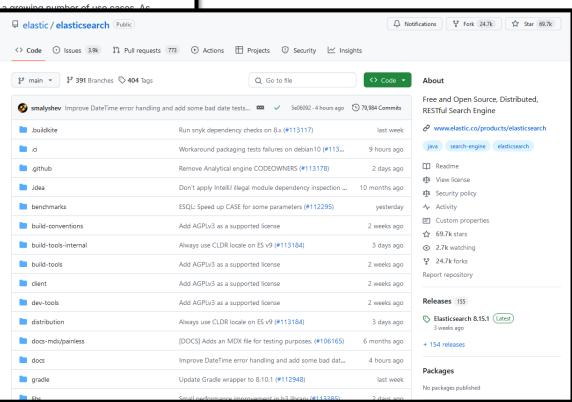
License
Who We are
TLP News

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Code of Conduct



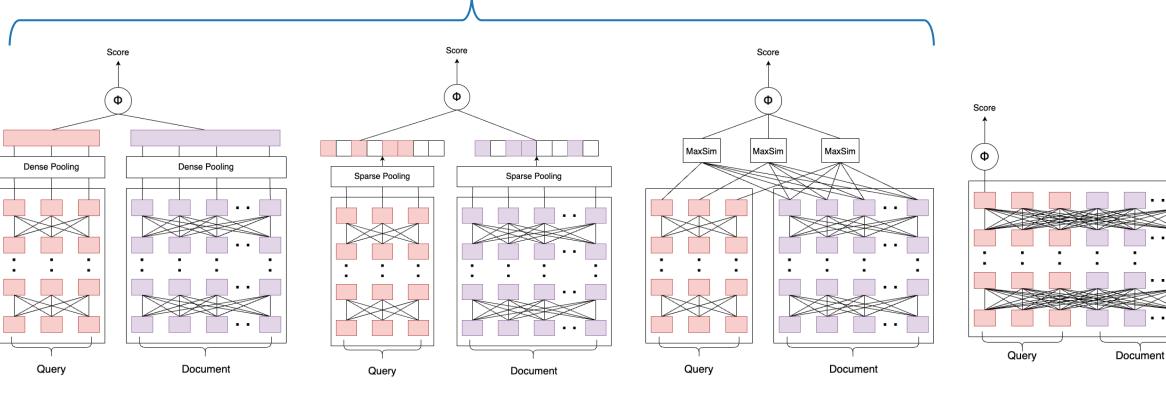
ANNOUNCEMENT: The Solr™ sub project has moved to a separate Top Level Project (TLP). All things Solr can now be found at https://solr.apache.org/. Mailing lists and git repositories have changed, please see details on the Solr website.



Can we go beyond surface forms?

neural language models





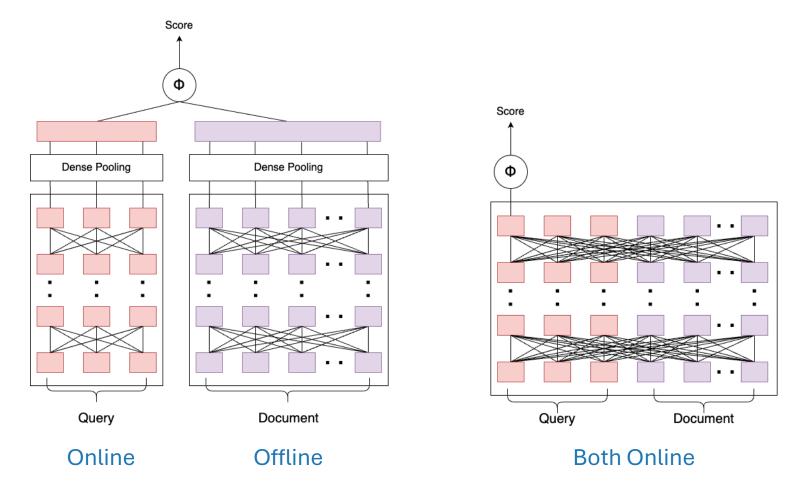
One Dense Vector Per Sequence e.g., DPR

One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

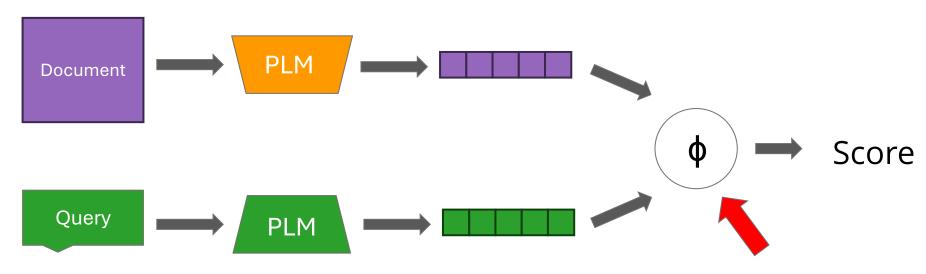
Multiple Dense Vectors Per Sequence e.g., ColBERT

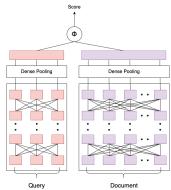
Joint Encoder e.g., monoBERT



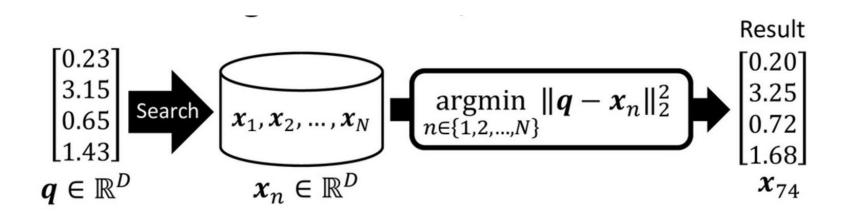
Separate query and document processing

One Vector per Query, One Vector per Document

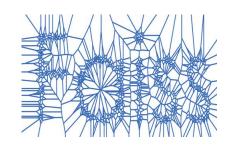




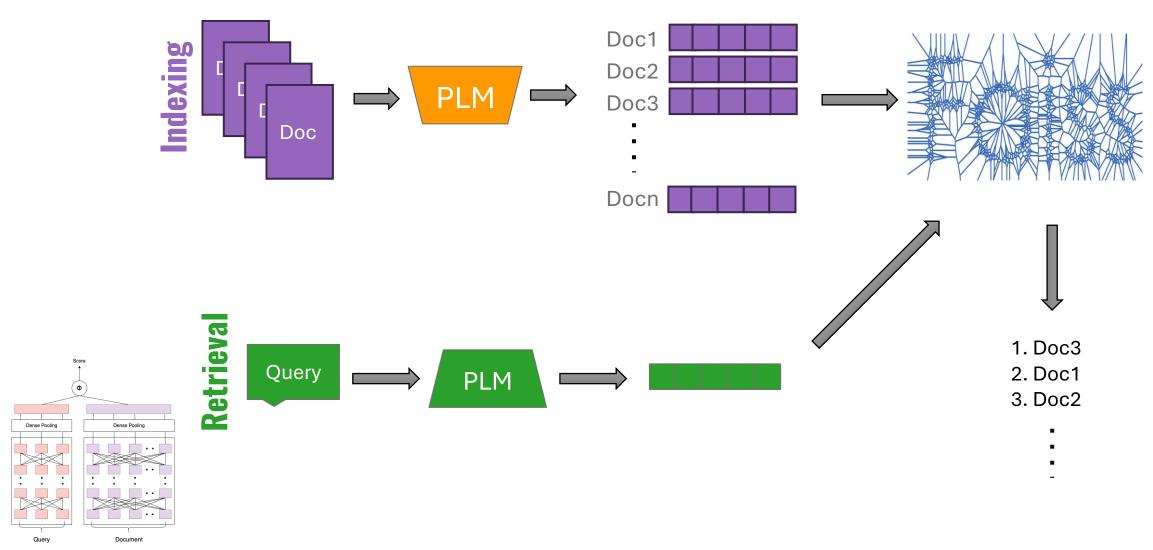
Nearest Vectors aka Neighbors



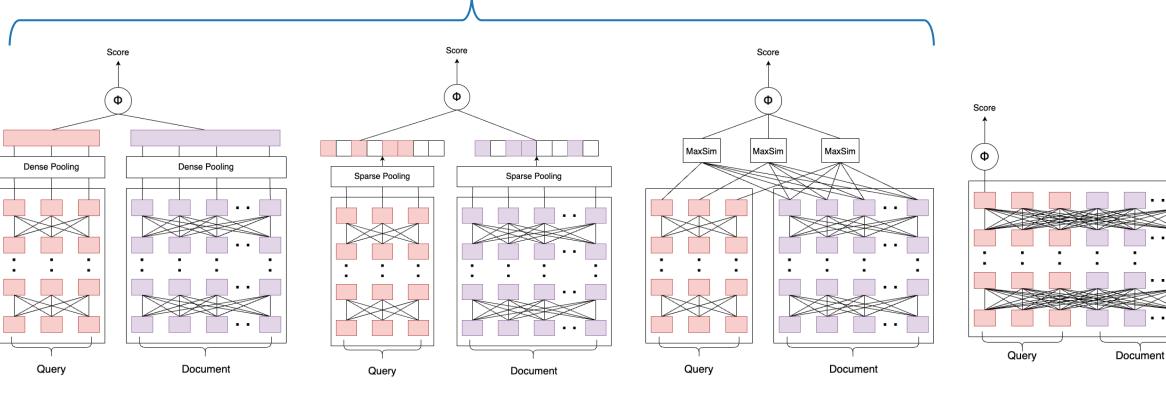
- Linear Search
 - Slow (scales linearly in size of document collection)
- Approximate Methods (e.g., Product Quantization) → ANN
 - Faster Search
- Runtime Efficiency vs Effectiveness



DPR Indexing and Retrieval







One Dense Vector Per Sequence e.g., DPR

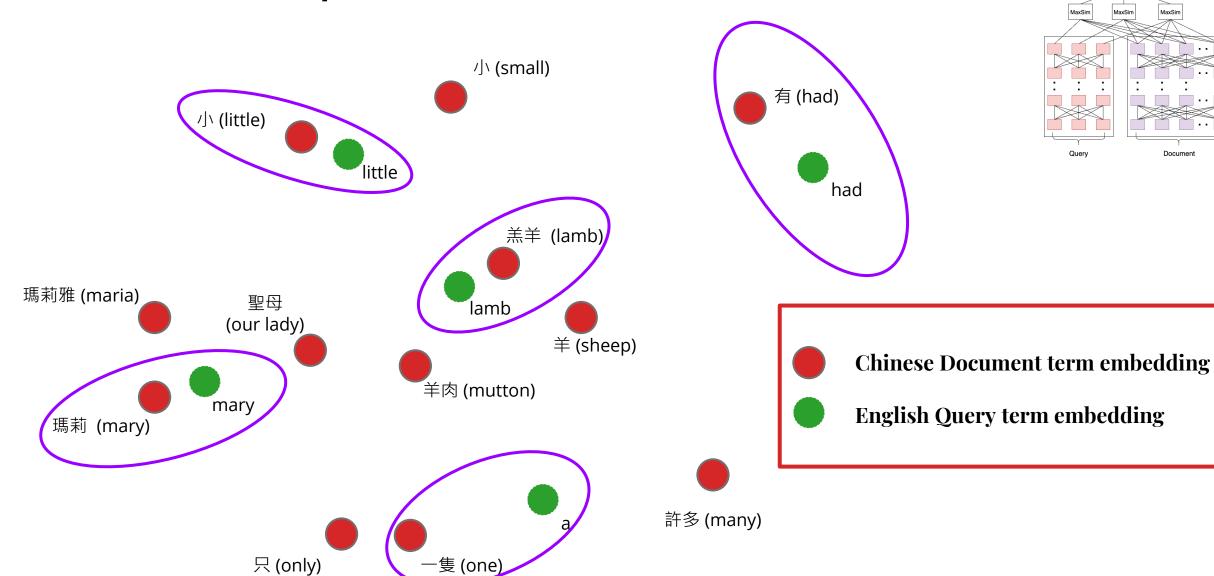
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

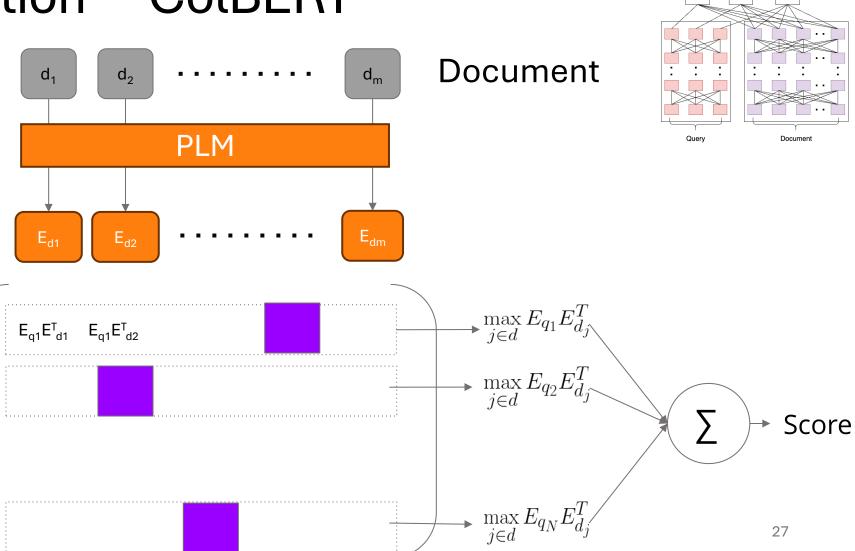
One Vector per Term: MaxSim



MaxSim in Action -- ColBERT

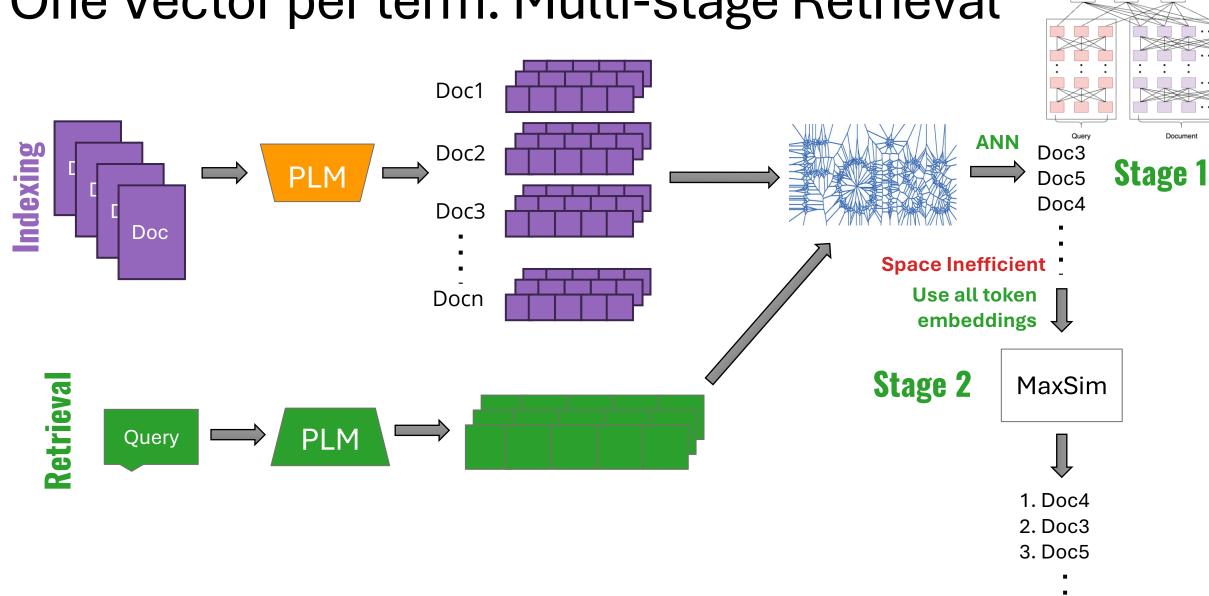
Query

 q_2



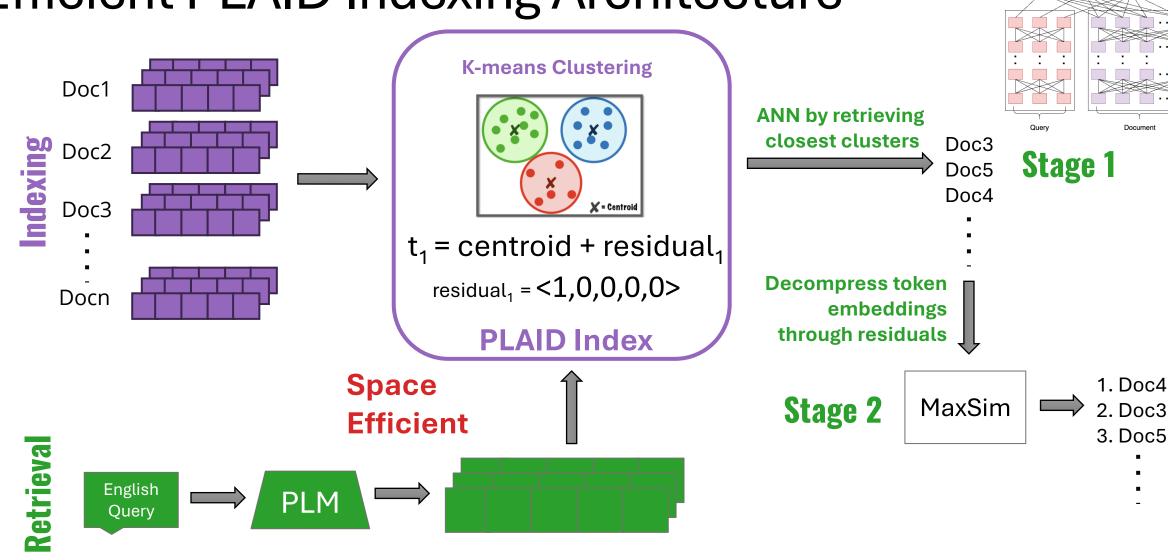
27

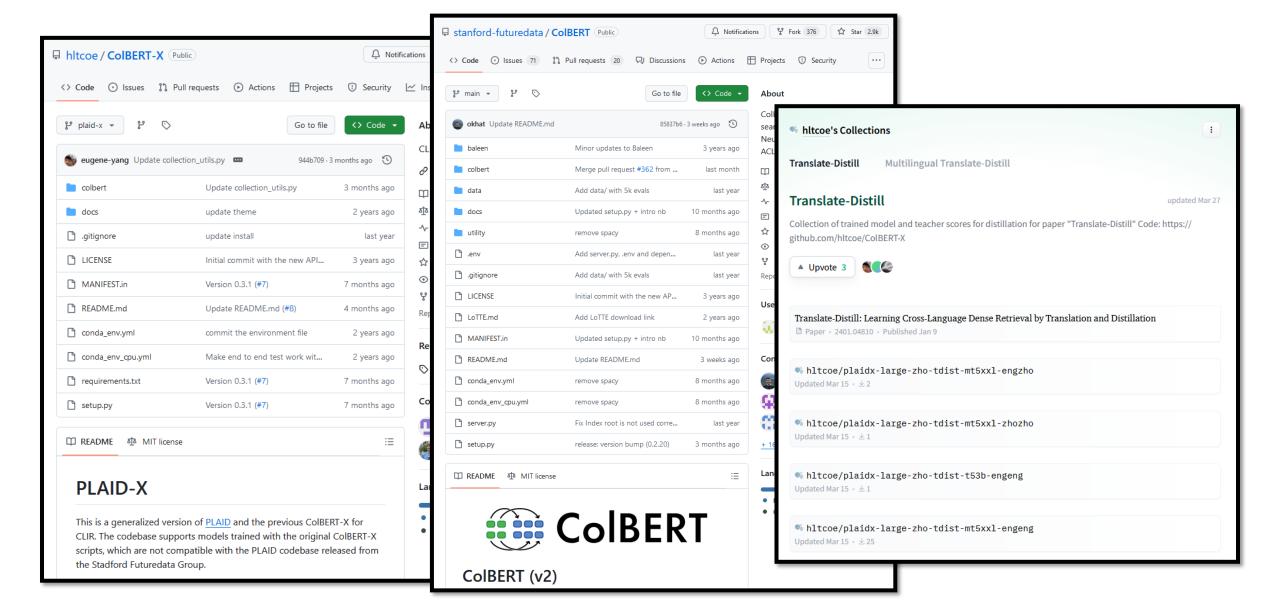
One Vector per term: Multi-stage Retrieval



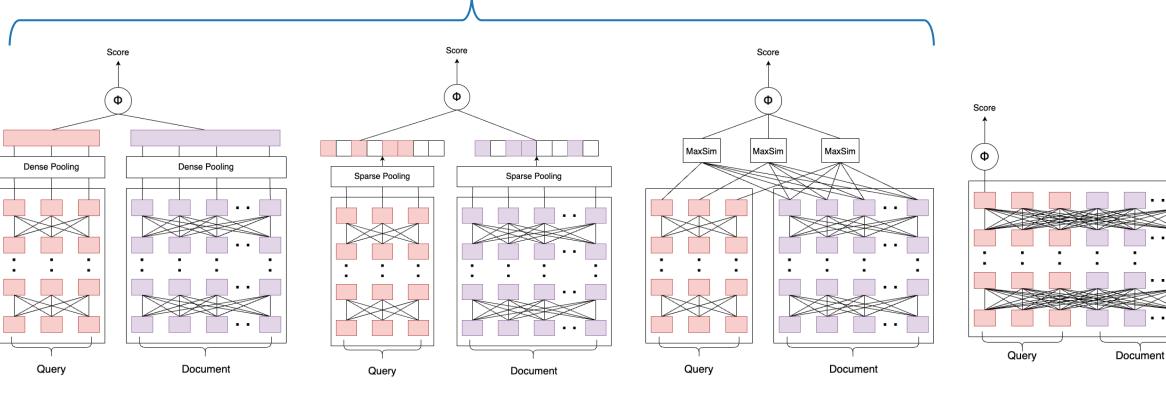
28

Efficient PLAID Indexing Architecture









One Dense Vector Per Sequence e.g., DPR

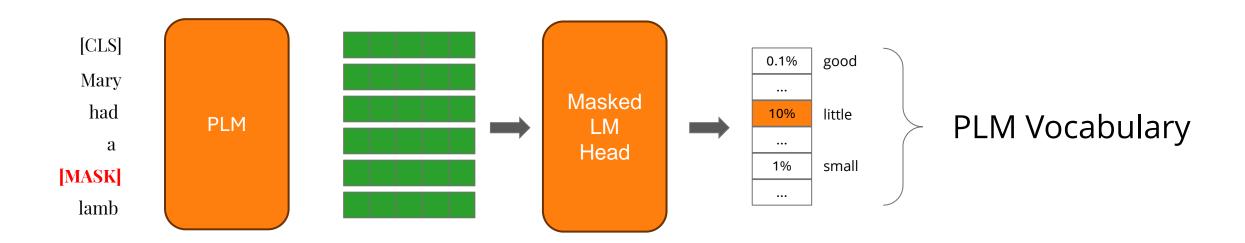
One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

High-dimensional Vector: Masked LM



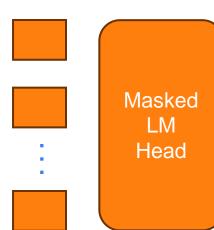
SPLADE

Baltimore Orioles clinch playoff berth for 2nd straight season

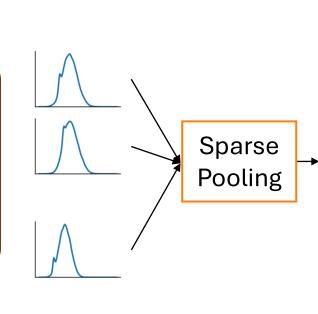
The Baltimore Orioles are headed to the playoffs in consecutive years for the first time since the 1990s, clinching no worse than a wild-card berth with a 5-3 win over the New York Yankees paired with Minnesota's loss to Miami



Baltimore Orioles' Anthony Santander runs the bases after hitting a home run during the sixth inning of a baseball game against the New York Yankees, Tuesday, Sept. 24, 2024, in New York. (AP Photo/Bryan Woolston)



PLM



Predicted Vocabulary

baltimore (1.2)

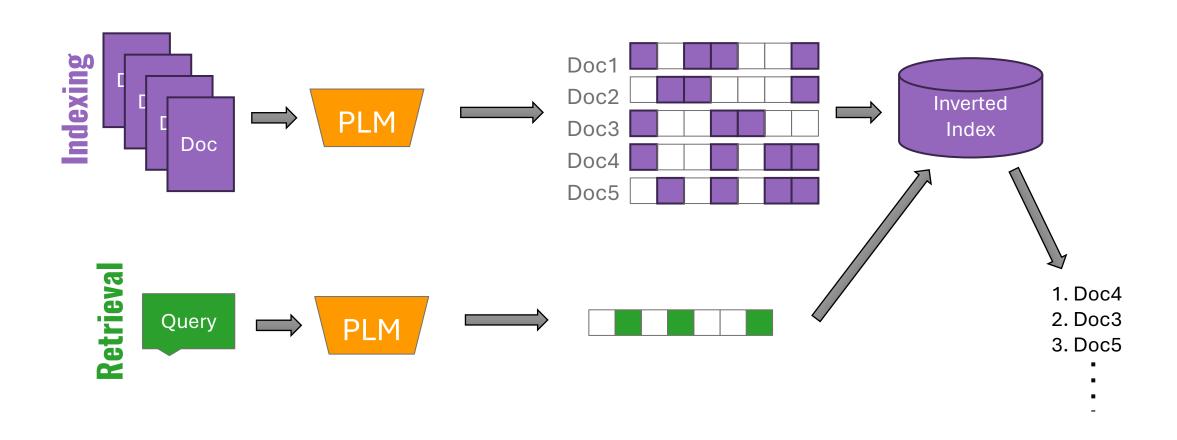
orioles (2.5)

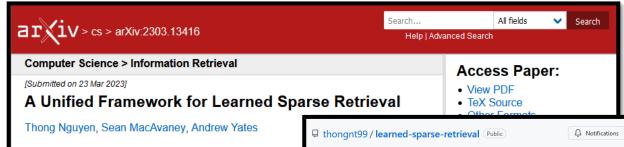
season (0.2)

berth (0.9)

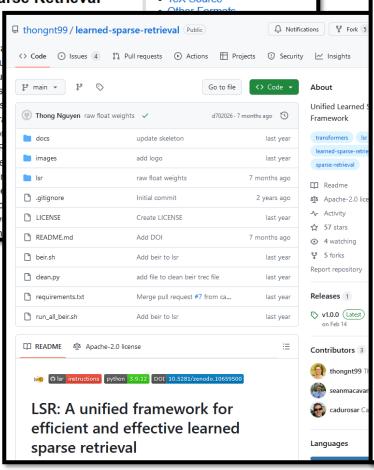
playoff (1.9)

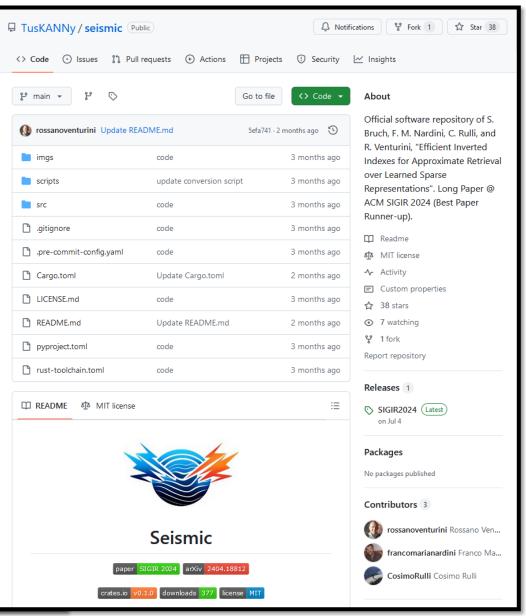
SPLADE Search Pipeline



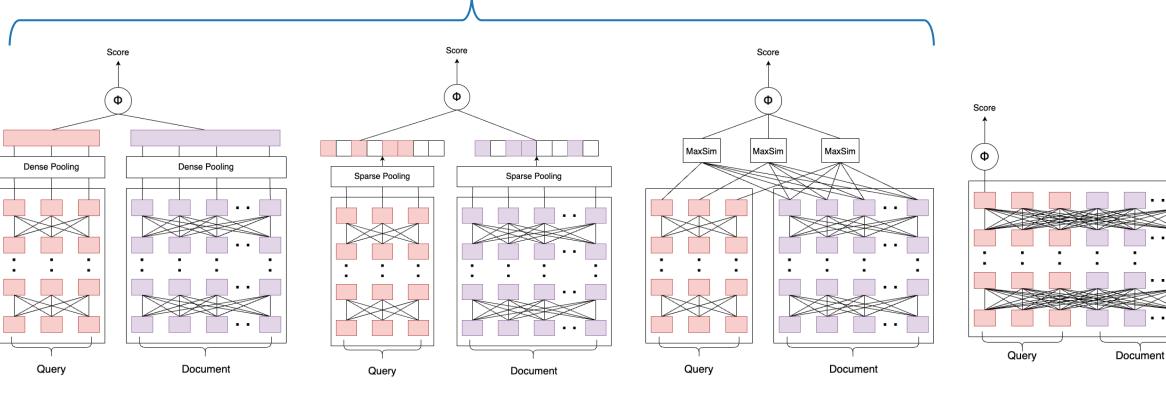


Learned sparse retrieval (LSR) is a family of first-stage retrieval to generate sparse lexical representations of queries and documented index. Many LSR methods have been recently introduce achieving state-of-the-art performance on MSMarco. Despite such architectures, many LSR methods show substantial differences efficiency. Differences in the experimental setups and configured difficult to compare the methods and derive insights. In this works methods and identify key components to establish an LSR LSR methods under the same perspective. We then reproduce using a common codebase and re-train them in the same environt to quantify how components of the framework affect effectivenes that (1) including document term weighting is most important for effectiveness, (2) including query weighting has a small positive document expansion and query expansion have a cancellation









One Dense Vector Per Sequence e.g., DPR

One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

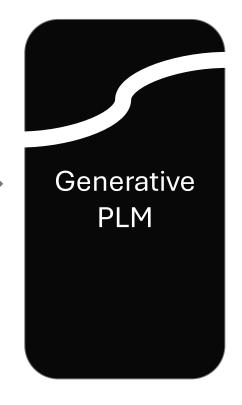
Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT

Cross-Encoder



Query: What does Mary has Doc: Mary had a little lamb. Relevant:



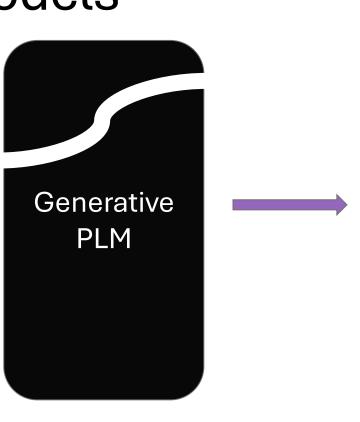
Not a number!

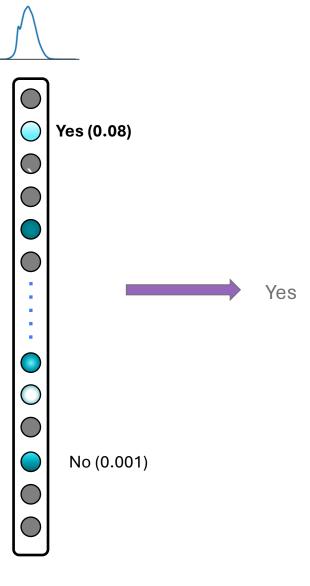
Yes

e.g, T5

Pradeep, Ronak, Rodrigo Nogueira, and Jimmy Lin. "The expando-mono-duo design pattern for text ranking with pretrained sequence-to-sequence models." arXiv preprint arXiv:2101.05667 (2021).

Query: What does Mary has Doc: Mary had a little lamb. Relevant:

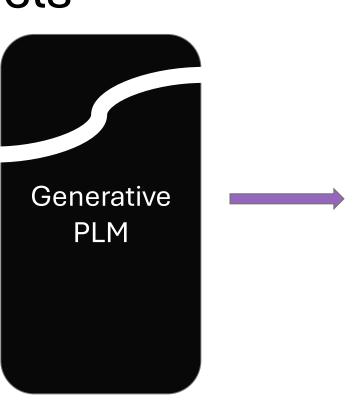




Pradeep, Ronak, Rodrigo Nogueira, and Jimmy Lin. "The expando-mono-duo design pattern for text ranking with pretrained sequence-to-sequence models." arXiv preprint arXiv:2101.05667 (2021).

Pointwise score

Query: What does Mary has Doc: Mary had a little lamb. Relevant:





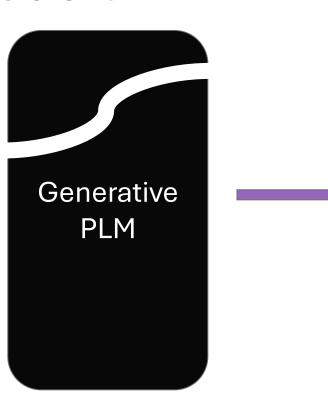
Yes (0.08)

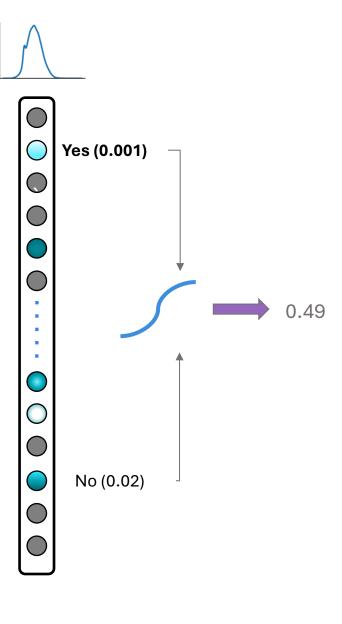
No (0.001)

Pairwise score

Query: What does Mary has Doc0: JHU is in Baltimore Doc1: Mary had a little lamb.

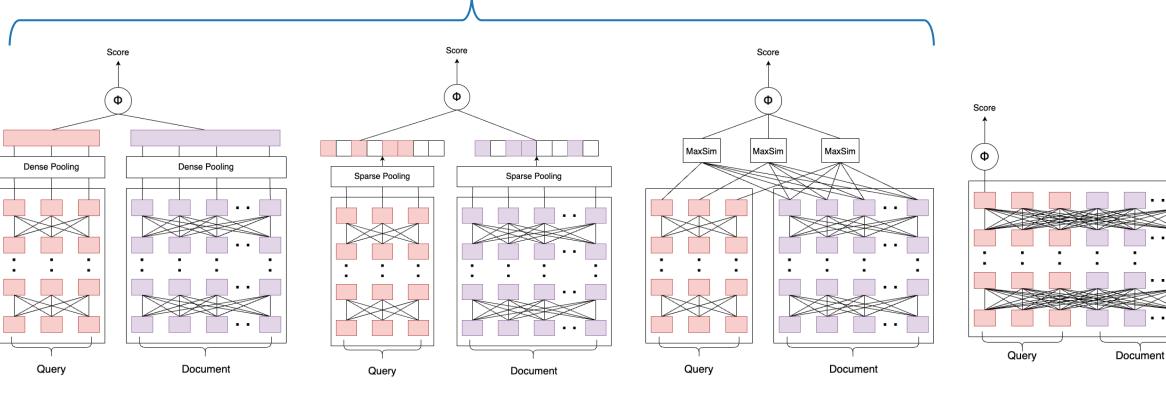
Relevant:





Pradeep, Ronak, Rodrigo Nogueira, and Jimmy Lin. "The expando-mono-duo design pattern for text ranking with pretrained sequence-to-sequence models." arXiv preprint arXiv:2101.05667 (2021).





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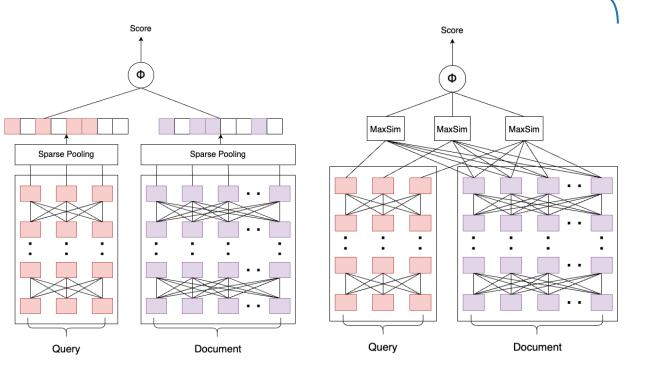
Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT

Joint Encoder e.g., monoBERT



Score



One Dense Vector Per Sequence e.g., DPR

Dense Pooling

Document

Dense Pooling

Query

One <u>Sparse</u> Vector Per Sequence e.g., SPLADE

Bi-Encoder

Multiple Dense Vectors Per Sequence e.g., ColBERT Joint Encoder e.g., monoBERT

Query

More Effective

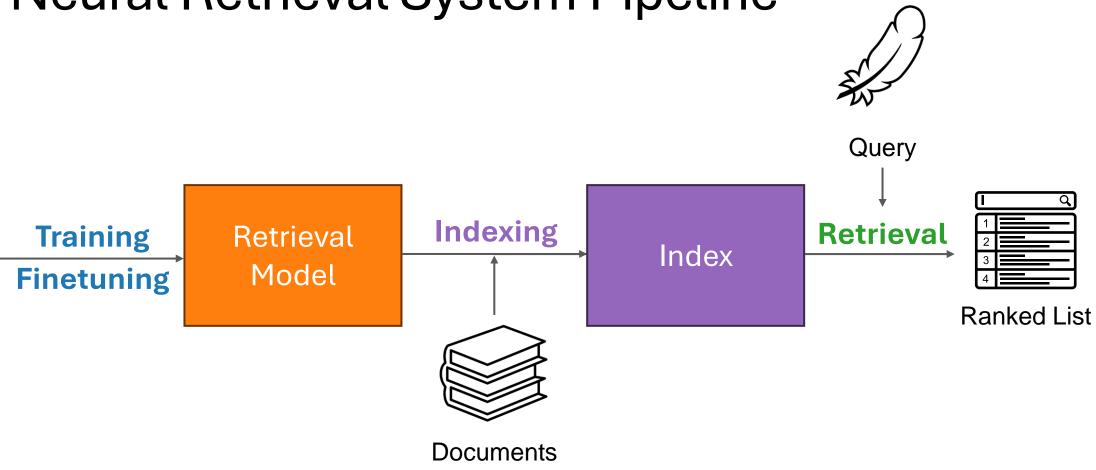
Document

More Efficient

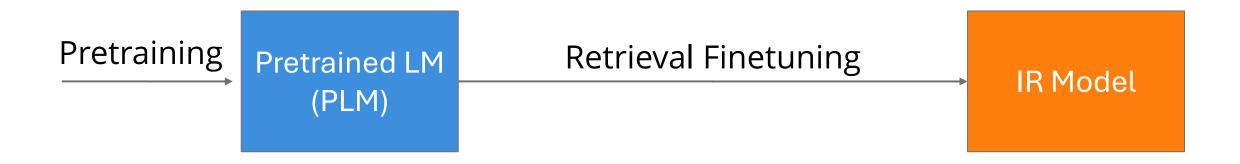
Retrieve-and-Rerank System Combinations



Neural Retrieval System Pipeline



PLM to IR Model



- Align the representation
- Model "relevancy"

Evaluation

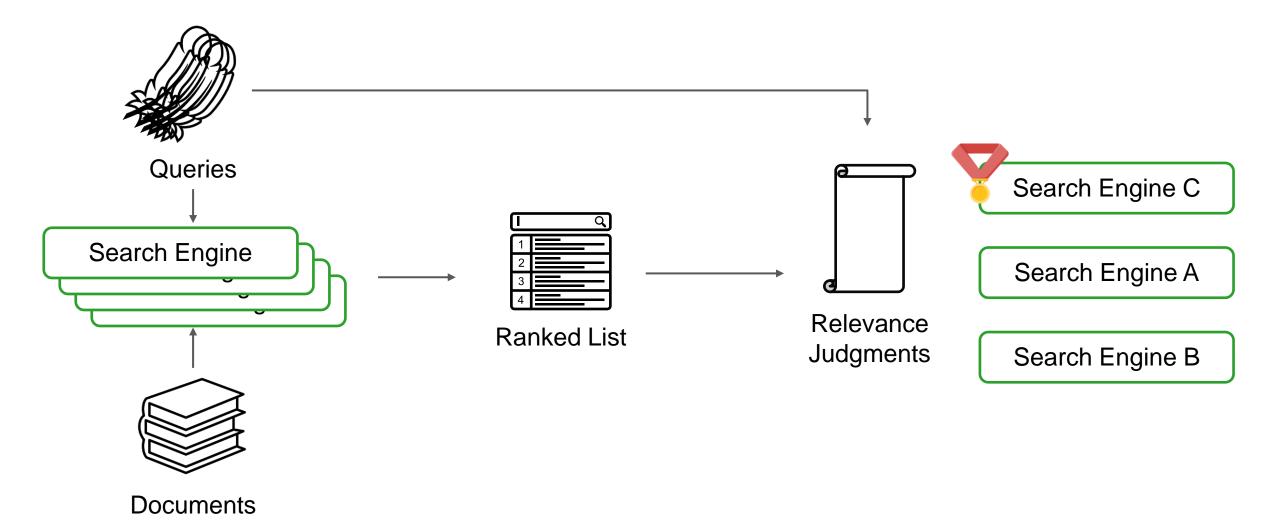
Which system is better?

What is Information Retrieval? (relevant)

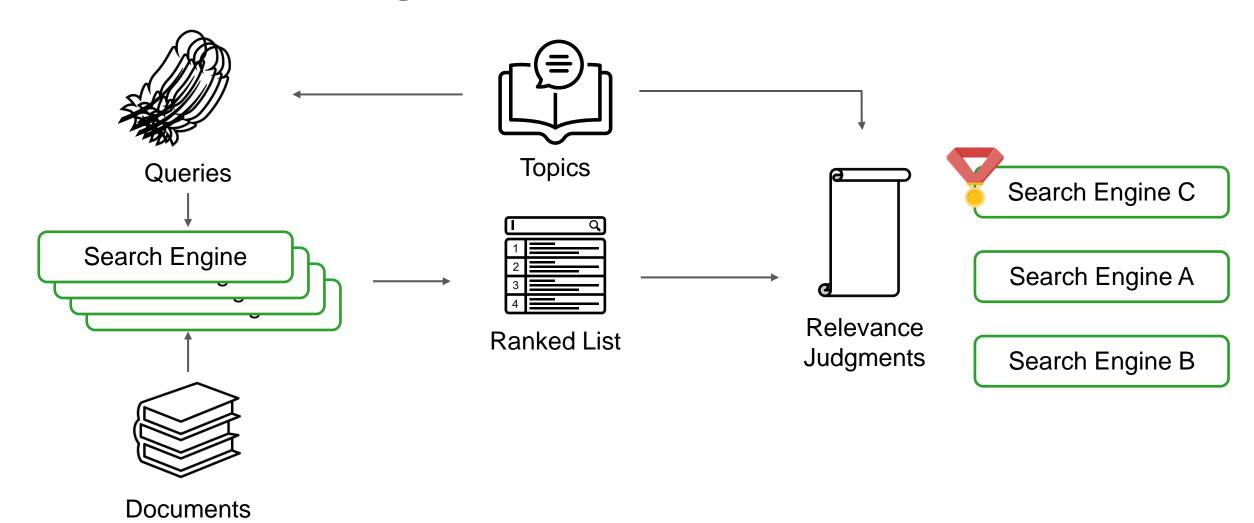
Retrieve information from a storage based on user's information need

Which system retrieve more relevant information?

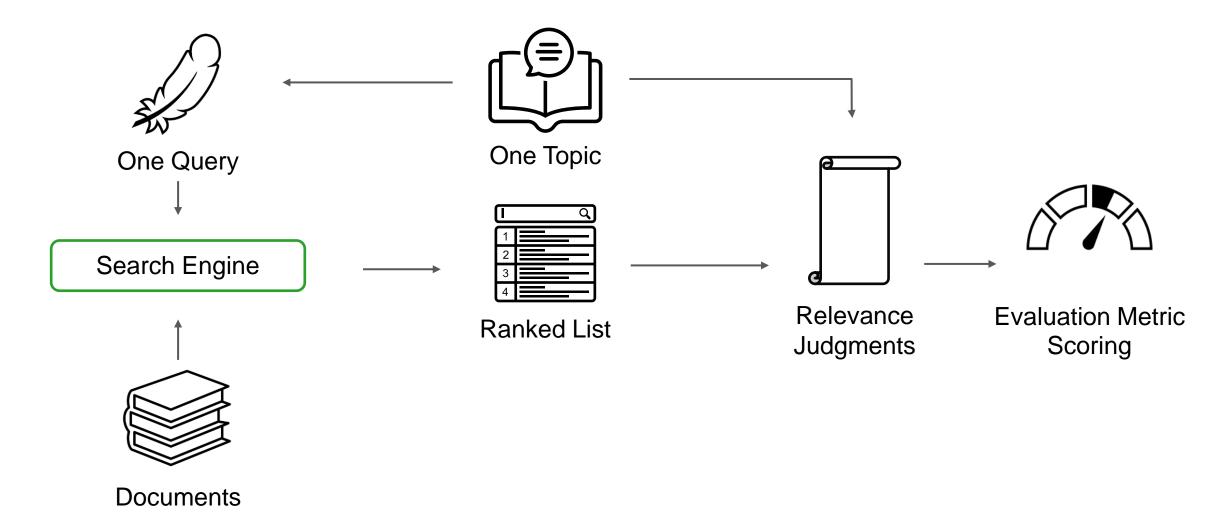
Cranfield Paradigm Evaluation



Cranfield Paradigm Evaluation



Cranfield Paradigm Evaluation



Differences

- Topics vs Queries
 - Clear intent vs an expression of such intent
- Relevance Judgements vs Labels
 - Opinion vs "fact"
- Ranked retrieval metrics
 - Measuring the quality/effectiveness of a ranked list

IR Metrics



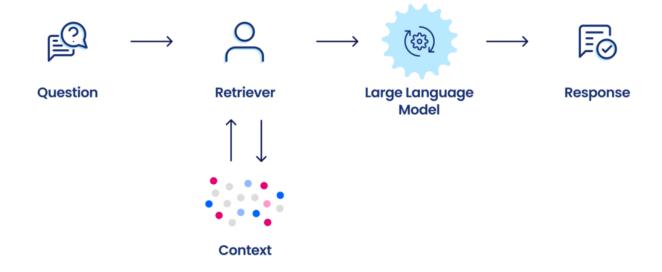
- Effective Metrics
 - Mean Average Precision
 - Normalized Discounted Cumulative Gain
 - Recall@k
- Efficiency Metrics
 - Indexing time
 - Index disk space
 - Query latency (average search time per query)

State of IR Research

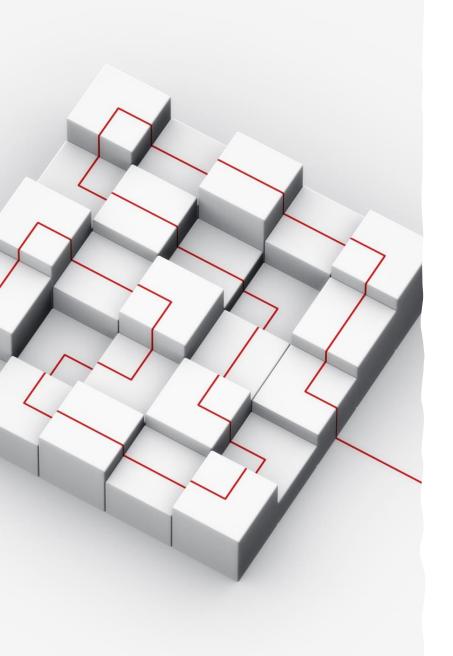
Retrieval-Augmented Generation

- Is everything a RAG problem?
- What is the right retrieval model/system for RAG?
- IR going away?

Retrieval Augmented Generation

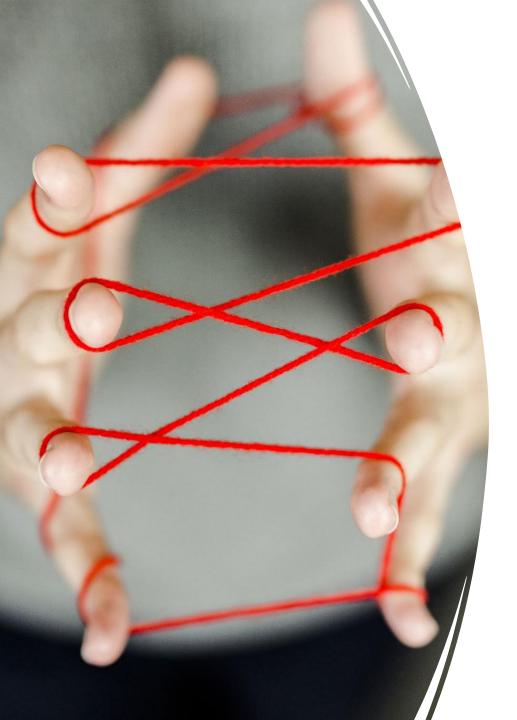


https://snorkel.ai/which-is-better-retrieval-augmentation-rag-or-fine-tuning-both/



Better Retrieval Models

- More effective
 - Better/larger neural models
 - Better architecture?
 - Under harder setup, e.g., scholar search, multilingual, cross-modal, etc
- More efficient
 - Faster at query time
 - Less resource footprint, e.g., memory, storage, compute, etc
- Other qualities
 - Fairness, diversity, etc



Other Retrieval Problems

- Conversational
 - Guessing intent, finding the "right" information to serve
- Iterative/interactive/human-in-the-loop
 - Rounds of interactions
- Generative
 - Returning a piece of text



Evaluation

- What to measure
 - and when would it fail
- How to measure
 - Generative text? Citations?
- "Better" evaluation collection
 - Not necessarily larger